

A novel machine learning model to predict abnormal Runway Occupancy Times and observe related precursors

Cologne EASA FDM conference

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Overview

- Introduction and Objective
- Approach
- Charles de Gaulle and Vienna data
- Methodology
- Conclusions and Recommendations
- Prototype live trial



Charles de Gaulle



Vienna

Introduction – need ATCO

Arrival mixed mode per single runway operation	Arrival Runway Occupancy Times (AROT)
Post processing	Sequence earlier MRAP (Multiple Runway Aiming Points)
1 min - 5 minutes	Tactical tool alert controller on extending AROT due to; <ul style="list-style-type: none">- Wind or bad visibility- Predicted missed runway exit- Runway excursion- Cut-off taxi ways leads to hold line up clearance for departure
+/- 15 min	Planning tool for departure only Sequence algorithm could change for arrival and flow departure
1 h – 3h	Strategic for ATCO supervisor (traffic manager) <ul style="list-style-type: none">- Coordination of the runway configuration- Selection criteria landing on which runway- Sequence algorithm could change- Input for AMAN/DMAN and flow manager

Can we better predict Arrival Runway Occupancy Time?

- We are working on solutions impacting the **Runway** for maintaining runway Arrival and Departure throughput
- As a first outcome of this process we have looked at “**better predicting the True airspeed profile, Time to fly and Taxi-Out Times**”
- This produced interesting first descriptive results
- This is the objective of my study....
- To develop a real time model that forecasts the *abnormal* Arrival Runway Occupancy Time (AROT) for different aircraft types, operational parameters and weather conditions.

Introduction - the problem

Unstable Approach



ATC Procedures



RECAT-EU

SUPER HEAVY	AH-124	A380
UPPER HEAVY	A332	B744
LOWER HEAVY	M011	B763
UPPER MEDIUM	B738	A320
LOWER MEDIUM	E190	A745
LIGHT	SF34	L335

Evaluation of feasible machine learning techniques for predicting the time to fly and aircraft speed profile on final approach

Predictive dynamic approach on final approach

7.7 Summary & 7.7.1 Summary

7.7.1 Summary

7.7.1.1 Summary

7.7.1.2 Summary

7.7.1.3 Summary

7.7.1.4 Summary

7.7.1.5 Summary

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7.7.1.98 Summary

7.7.1.99 Summary

7.7.1.100 Summary

Taxi-Out Time prediction model through machine learning techniques at Charles de Gaulle airport

Taxi-Out Time prediction model through machine learning techniques at Charles de Gaulle airport

From: Thomas, J. and Richard, C. (2018) 'Taxi-Out Time prediction model through machine learning techniques at Charles de Gaulle airport', *Journal of Air Transport Management*, vol. 70, pp. 1-10.

Abstract: This paper presents a machine learning model for predicting taxi-out times at Charles de Gaulle airport. The model is based on a large dataset of taxi-out times and various input variables. The model is trained using a neural network and is able to predict taxi-out times with a high degree of accuracy. The model is evaluated using a cross-validation technique and is found to be a good predictor of taxi-out times.

Taxi-Out Times



Runway will focus on the following sub scenarios since these are the most limiting factors

Runway excursion



Runway Occupancy Time



Reduction of Separation



TYPICAL ADDITIONAL SPACING-BUFFER TO APPLY AT 4046 FOR DELIVERING-SEPARATION MINIMA

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A novel machine learning model to predict abnormal Runway Occupancy Times and observe related precursors

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Abstract: This paper presents a machine learning model for predicting abnormal runway occupancy times (ART) at Charles de Gaulle airport. The model is based on a large dataset of ART and various input variables. The model is trained using a neural network and is able to predict ART with a high degree of accuracy. The model is evaluated using a cross-validation technique and is found to be a good predictor of ART.

Introduction - the problem

Unstable Approach



ATC Procedures



RECAT-EU

SUPER HEAVY	AH-124	A380
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Evaluation of feasible machine learning techniques for predicting the time to fly and aircraft speed profile on final approach

TT Runway 9.7.7 Time
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Abstract
This paper presents a novel machine learning (ML) technique for predicting the time to fly (TTF) and aircraft speed profile on final approach. The proposed method is based on a deep neural network (DNN) architecture, which is trained on a large dataset of flight data. The results show that the proposed method outperforms traditional methods in terms of prediction accuracy and computational efficiency.

Keywords
Machine Learning, Deep Neural Network, Time to Fly, Aircraft Speed Profile, Final Approach.

1. Introduction
The time to fly (TTF) and aircraft speed profile on final approach are critical parameters for air traffic control (ATC) and runway management. Accurate prediction of these parameters is essential for ensuring safe and efficient flight operations. This paper presents a novel machine learning (ML) technique for predicting the TTF and aircraft speed profile on final approach.

2. Related Work
Several studies have been conducted in the field of TTF and aircraft speed profile prediction. These studies have used various ML techniques, including linear regression, decision trees, and neural networks. However, these methods have limited predictive power and are often computationally expensive.

Taxi-Out Times



In this study we focus on the contributing factor
Arrival Runway Occupancy Times

Runway excursion



Runway Occupancy Time



A novel machine learning model to predict abnormal Runway Occupancy Times and observe related precursors

Abstract
This paper presents a novel machine learning (ML) model for predicting abnormal runway occupancy times (ROWT) and observing related precursors. The proposed model is based on a deep neural network (DNN) architecture, which is trained on a large dataset of flight data. The results show that the proposed model outperforms traditional methods in terms of prediction accuracy and computational efficiency.

Keywords
Machine Learning, Deep Neural Network, Runway Occupancy Time, Precursors.

1. Introduction
Runway occupancy time (ROWT) is a critical parameter for air traffic control (ATC) and runway management. Accurate prediction of ROWT is essential for ensuring safe and efficient flight operations. This paper presents a novel machine learning (ML) model for predicting abnormal ROWT and observing related precursors.

Taxi-Out Time prediction model through machine learning techniques at Charles de Gaulle airport

Abstract
This paper presents a novel machine learning (ML) model for predicting taxi-out times (TOT) at Charles de Gaulle airport. The proposed model is based on a deep neural network (DNN) architecture, which is trained on a large dataset of flight data. The results show that the proposed model outperforms traditional methods in terms of prediction accuracy and computational efficiency.

Keywords
Machine Learning, Deep Neural Network, Taxi-Out Time, Charles de Gaulle Airport.

1. Introduction
Taxi-out time (TOT) is a critical parameter for air traffic control (ATC) and runway management. Accurate prediction of TOT is essential for ensuring safe and efficient flight operations. This paper presents a novel machine learning (ML) model for predicting TOT at Charles de Gaulle airport.

2. Related Work
Several studies have been conducted in the field of TOT prediction. These studies have used various ML techniques, including linear regression, decision trees, and neural networks. However, these methods have limited predictive power and are often computationally expensive.

3. Methodology
The proposed model is based on a deep neural network (DNN) architecture, which is trained on a large dataset of flight data. The model consists of an input layer, a hidden layer, and an output layer. The input layer takes as input various parameters related to the flight, such as aircraft type, weight, and wind speed. The hidden layer consists of multiple nodes, each representing a different feature of the flight. The output layer produces the predicted TOT.

4. Results and Discussion
The results of the experiment show that the proposed model outperforms traditional methods in terms of prediction accuracy and computational efficiency. The model is able to predict TOT with a high degree of accuracy, even in the presence of noise and outliers in the data.

5. Conclusion
This paper presents a novel machine learning (ML) model for predicting taxi-out times (TOT) at Charles de Gaulle airport. The proposed model is based on a deep neural network (DNN) architecture, which is trained on a large dataset of flight data. The results show that the proposed model outperforms traditional methods in terms of prediction accuracy and computational efficiency.

6. Acknowledgments
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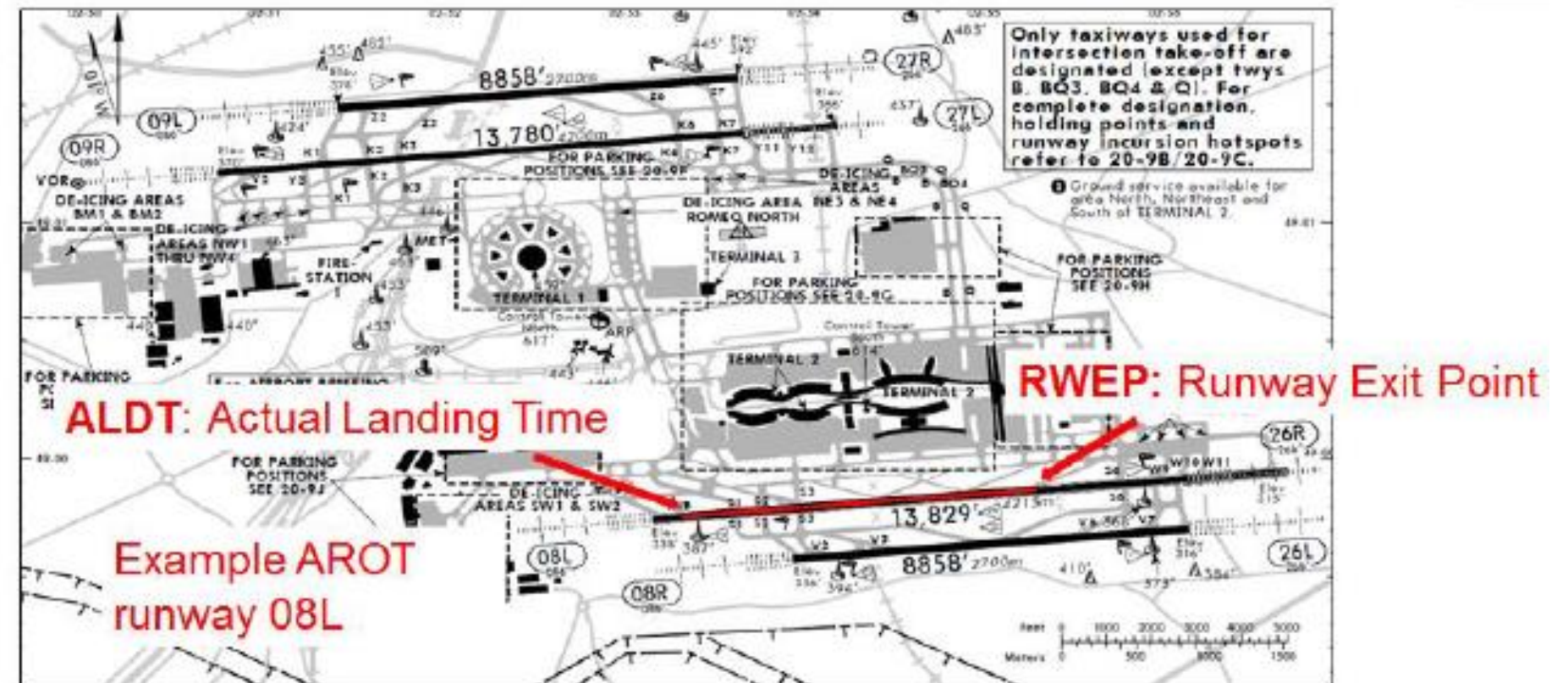
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JOINT UNDERTAKING

Introduction – Approach & Methodology

- Consider real data from Charles de Gaulle (CDG) airport
- 2 year of data (2014/2015)
- Assess AROT for each possible Runway and Aircraft type
- For instance:
 - Air France A320 from London
 - Runway 08L
 - Start prediction 08:00
 - Update frequency 5 min
 - Number of simulations 1500



Data collection CDG

■ 350,000 Arrival flights from CDG

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Jour	Mois	Année	Identifiant	Numéro de	Immatriculation	Code OAC	Code IATA	Compagnie	Code aéroport	Code aéroport	Horaire Bloc	Horaire Piste	Horaire Théorique	SOBT / SIBT	EOBT / EIBT	TOBT	AOBT / AIBT	CTOT
2	01-01-2015	1	2015	AFR007	AF007	FHPJB	AFR	AF	AIR FRANCE	KJFK	JFK	01-01-2015 07:49	01-01-2015 07:35	01-01-2015 08:30	01-01-2015 08:30	01-01-2015 07:56		01-01-2015 07:49	
3	01-01-2015	1	2015	AFR293	AF293	FGSPU	AFR	AF	AIR FRANCE	RJTT	HND	01-01-2015 05:14	01-01-2015 05:05	01-01-2015 05:30	01-01-2015 05:30	01-01-2015 05:23		01-01-2015 05:14	
4	01-01-2015	1	2015	AFR6741	AF6741	FGUOB	AFR	AF	AIR FRANCE	FCBB	BZV	01-01-2015 05:26	01-01-2015 05:17	01-01-2015 05:40	01-01-2015 05:40	01-01-2015 05:23		01-01-2015 05:26	
5	01-01-2015	1	2015	AFR463	AF463	FGZNL	AFR	AF	AIR FRANCE	FIMP	MRU	01-01-2015 05:21	01-01-2015 05:11	01-01-2015 05:45	01-01-2015 05:45	01-01-2015 05:18		01-01-2015 05:21	
6	01-01-2015	1	2015	AFR833	AF833	FGZCG	AFR	AF	AIR FRANCE	FCPP	PNR	01-01-2015 05:54	01-01-2015 05:46	01-01-2015 06:00	01-01-2015 06:00	01-01-2015 05:54		01-01-2015 05:54	
7	01-01-2015	1	2015	AFR755	AF755	FGZCH	AFR	AF	AIR FRANCE	GUCY	CKY	01-01-2015 05:49	01-01-2015 05:37	01-01-2015 06:05	01-01-2015 06:05	01-01-2015 05:51		01-01-2015 05:49	
8	01-01-2015	1	2015	AFR225	AF225	FGSPQ	AFR	AF	AIR FRANCE	VIDP	DEL	01-01-2015 06:02	01-01-2015 05:55	01-01-2015 06:10	01-01-2015 06:10	01-01-2015 06:02		01-01-2015 06:02	
9	01-01-2015	1	2015	AFR719	AF719	FGZNI	AFR	AF	AIR FRANCE	GOOY	DKR	01-01-2015 06:21	01-01-2015 06:10	01-01-2015 06:15	01-01-2015 06:15	01-01-2015 06:18		01-01-2015 06:21	
10	01-01-2015	1	2015	AFR561	AF561	FGLZC	AFR	AF	AIR FRANCE	OLBA	BEY	01-01-2015 13:41	01-01-2015 13:36	01-01-2015 14:00	01-01-2015 14:00	01-01-2015 13:48		01-01-2015 13:41	
11	02-01-2015	1	2015	AFR445	AF445	FGZCJ	AFR	AF	AIR FRANCE	SBGL	GIG	02-01-2015 11:50	02-01-2015 11:42	02-01-2015 11:35	02-01-2015 11:35	02-01-2015 11:39		02-01-2015 11:50	
12	02-01-2015	1	2015	AFR1497	AF1497	FGKXJ	AFR	AF	AIR FRANCE	GMMN	CMN	02-01-2015 11:26	02-01-2015 11:20	02-01-2015 11:35	02-01-2015 11:35	02-01-2015 11:30		02-01-2015 11:26	
13	02-01-2015	1	2015	AFR503	AF503	FGSPS	AFR	AF	AIR FRANCE	HECA	CAI	02-01-2015 11:19	02-01-2015 11:05	02-01-2015 11:35	02-01-2015 11:35	02-01-2015 11:13		02-01-2015 11:19	
14	02-01-2015	1	2015	AFR459	AF459	FGSQF	AFR	AF	AIR FRANCE	SBGR	GRU	02-01-2015 11:47	02-01-2015 11:34	02-01-2015 11:35	02-01-2015 11:35	02-01-2015 11:40		02-01-2015 11:47	
15	02-01-2015	1	2015	ROT381U	RO381	YRBGA	ROT	RO	TAROM	ROLROP	OTP	02-01-2015 11:48	02-01-2015 11:30	02-01-2015 11:35	02-01-2015 11:35	02-01-2015 11:45		02-01-2015 11:48	
16	02-01-2015	1	2015	AFL2454	SU2454	VQBIW	AFL	SU	AEROFLOT	UUEE	SVO	02-01-2015 12:21	02-01-2015 12:16	02-01-2015 12:25	02-01-2015 12:25	02-01-2015 12:33		02-01-2015 12:21	
17	03-01-2015	1	2015	AF751QJ	AF7751	FHBXG	AFR	AF	AIR FRANCE	LFLC	CFE	03-01-2015 08:00	03-01-2015 07:49	03-01-2015 07:50	03-01-2015 07:50	03-01-2015 08:00		03-01-2015 08:00	
18	03-01-2015	1	2015	AFR1911	AF1911	EIRJU	AFR	AF	AIR FRANCE	EDDN	NUE	03-01-2015 08:05	03-01-2015 07:51	03-01-2015 07:50	03-01-2015 07:50	03-01-2015 08:01		03-01-2015 08:05	
19	03-01-2015	1	2015	AF737EW	AF7737	FGUGC	AFR	AF	AIR FRANCE	LFRB	BES	03-01-2015 07:53	03-01-2015 07:43	03-01-2015 07:50	03-01-2015 07:50	03-01-2015 07:52		03-01-2015 07:53	
20	03-01-2015	1	2015	UAE71	EK071	A6EEY	UAE	EK	EMIRATES	OMDB	DXB	03-01-2015 08:26	03-01-2015 08:19	03-01-2015 07:50	03-01-2015 07:50	03-01-2015 08:12		03-01-2015 08:26	
21	03-01-2015	1	2015	AWE754	US754	N276AY	AWE	US	US AIRWAYS	KLAX	LAX	03-01-2015 07:15	03-01-2015 07:07	03-01-2015 07:55	03-01-2015 07:55	03-01-2015 06:55		03-01-2015 07:15	
22	03-01-2015	1	2015	AFR1503	AF1503	EIRJF	AFR	AF	AIR FRANCE	LIMF	TRN	03-01-2015 08:05	03-01-2015 07:54	03-01-2015 07:55	03-01-2015 07:55	03-01-2015 08:05		03-01-2015 08:05	
23	03-01-2015	1	2015	AFR347	AF347	FGLZK	AFR	AF	AIR FRANCE	CYUL	YUL	03-01-2015 07:28	03-01-2015 07:08	03-01-2015 07:55	03-01-2015 07:55	03-01-2015 07:13		03-01-2015 07:28	
24	03-01-2015	1	2015	AFR061E	AF1611	FGUGI	AFR	AF	AIR FRANCE	EDDH	HAM	03-01-2015 07:53	03-01-2015 07:38	03-01-2015 07:55	03-01-2015 07:55	03-01-2015 07:51		03-01-2015 07:53	
25	03-01-2015	1	2015	AFR1725	AF1725	FHBXL	AFR	AF	AIR FRANCE	EDDW	BRE	03-01-2015 07:55	03-01-2015 07:42	03-01-2015 08:00	03-01-2015 08:00	03-01-2015 07:44		03-01-2015 07:55	
26	03-01-2015	1	2015	AFR443	AF443	FGZNI	AFR	AF	AIR FRANCE	SBGL	GIG	03-01-2015 07:48	03-01-2015 07:37	03-01-2015 08:00	03-01-2015 08:00	03-01-2015 07:42		03-01-2015 07:48	
27	03-01-2015	1	2015	AF681VC	AF7681	FGTAL	AFR	AF	AIR FRANCE	LFMT	MPL	03-01-2015 08:05	03-01-2015 07:57	03-01-2015 08:00	03-01-2015 08:00	03-01-2015 08:09		03-01-2015 08:05	
28	03-01-2015	1	2015	DAL270	DL270	N174DN	DAL	DL	DELTA AIR	KEWR	EWR	03-01-2015 07:19	03-01-2015 07:11	03-01-2015 08:00	03-01-2015 08:00	03-01-2015 07:14		03-01-2015 07:19	
29	03-01-2015	1	2015	AFR351	AF351	FGLZN	AFR	AF	AIR FRANCE	CYYZ	YYZ	03-01-2015 07:47	03-01-2015 07:33	03-01-2015 08:05	03-01-2015 08:05	03-01-2015 07:33		03-01-2015 07:47	

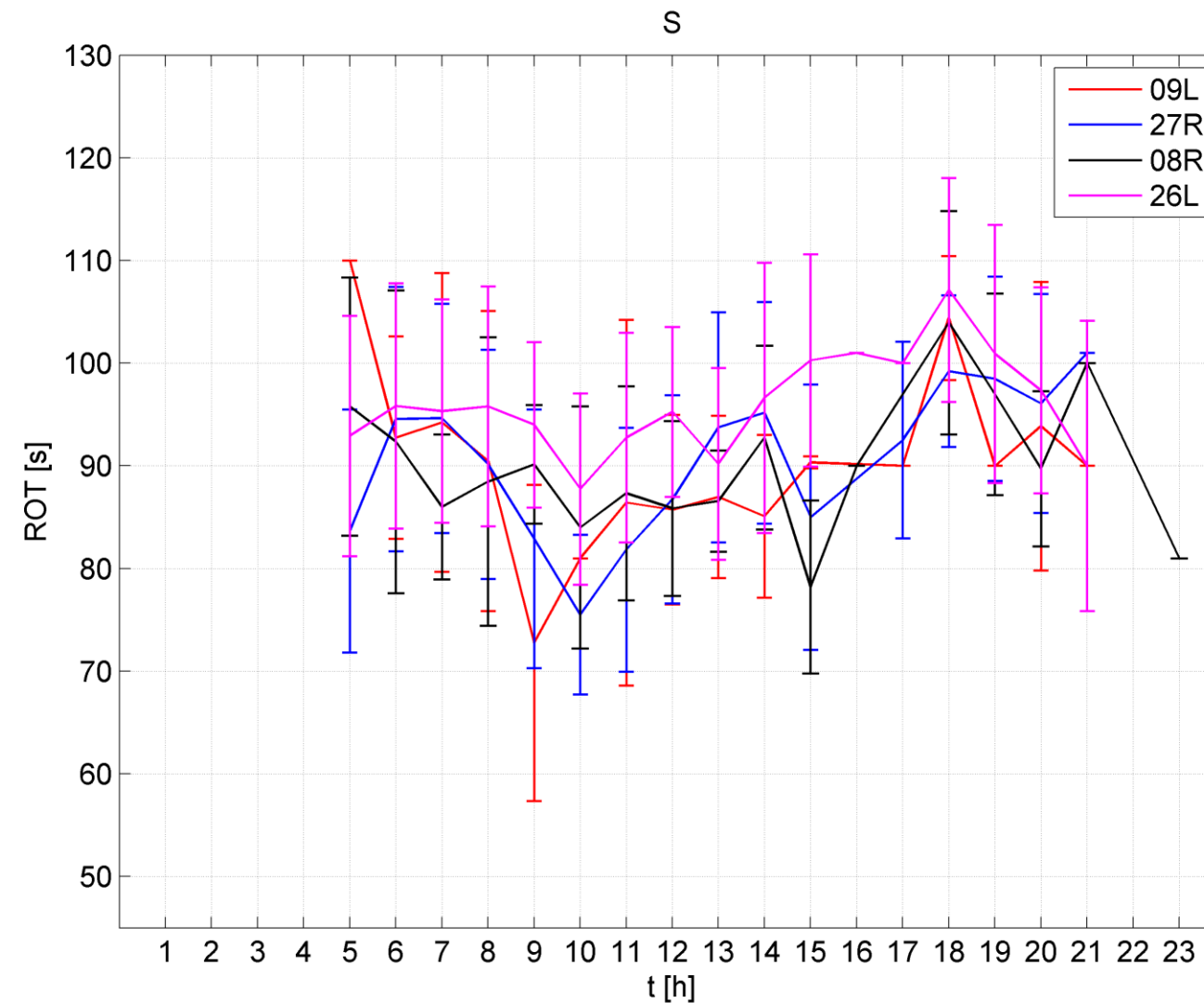
Data collection CDG

- 350,000 Arrival flights from CDG

	DETECTIO	DETECTION_ZO	HEURE_DETECTÉE	VOL_LIBELLE	CIE_CLE	NVOL_LIG_NUM	TAS_GLOB	NVOL_MV	TA_CLE	IM_IMMA	VOL_ID_A	VOL_DT_OR	VOL_DT_EXP	VOL_HTAD_LT	ALDT/ATOT	QFU_COD	TA_OACI	VITESSE(m/s)	
	ENTR_CATT3		29-09-2015 12:02	ME210	ME	210	C2C	D	332	ODMED	MEA210	29-09-2015	29-09-2015	29-09-2015 10:00	29-09-2015 12:04	08L	A332	1	
	OVERD	26R	29-09-2015 12:04	ME210	ME	210	C2C	D	332	ODMED	MEA210	29-09-2015	29-09-2015	29-09-2015 10:00	29-09-2015 12:04	08L	A332	7.308.234	
	OVERD	26R-LLZ	29-09-2015 12:04	ME210	ME	210	C2C	D	332	ODMED	MEA210	29-09-2015	29-09-2015	29-09-2015 10:00	29-09-2015 12:04	08L	A332	7.308.234	
	OVERD	26R-1NM	29-09-2015 12:05	ME210	ME	210	C2C	D	332	ODMED	MEA210	29-09-2015	29-09-2015	29-09-2015 10:00	29-09-2015 12:04	08L	A332	6.945.892	
	OVERD	26R-2NM	29-09-2015 12:05	ME210	ME	210	C2C	D	332	ODMED	MEA210	29-09-2015	29-09-2015	29-09-2015 10:00	29-09-2015 12:04	08L	A332	6.783.306	
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	ENTR_CATT3		29-09-2015 11:40	AF976	AF	976	C2E	D	77W	FGSQG	AFR976	29-09-2015	29-09-2015	29-09-2015 10:40	29-09-2015 11:44	08L	B77W	5.653.821	
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	OVERD	26R-1NM	29-09-2015 11:44	AF976	AF	976	C2E	D	77W	FGSQG	AFR976	29-09-2015	29-09-2015	29-09-2015 10:40	29-09-2015 11:44	08L	B77W	8.158.048	
	OVERD	26R-2NM	29-09-2015 11:45	AF976	AF	976	C2E	D	77W	FGSQG	AFR976	29-09-2015	29-09-2015	29-09-2015 10:40	29-09-2015 11:44	08L	B77W	809.034	
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	OVERD	26R	29-09-2015 13:44	AF1620	AF	1620	C2E	D	320	FHEPD	AFR1620	29-09-2015	29-09-2015	29-09-2015 10:50	29-09-2015 13:44	08L	A320	7.518.154	
	OVERD	26R-LLZ	29-09-2015 13:44	AF1620	AF	1620	C2E	D	320	FHEPD	AFR1620	29-09-2015	29-09-2015	29-09-2015 10:50	29-09-2015 13:44	08L	A320	7.518.154	
	OVERD	26R-1NM	29-09-2015 13:44	AF1620	AF	1620	C2E	D	320	FHEPD	AFR1620	29-09-2015	29-09-2015	29-09-2015 10:50	29-09-2015 13:44	08L	A320	7.355.412	
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	OVERD	26R-1NM	29-09-2015 11:47	EY032	EY	32	C2C	D	77W	A6ETN	ETD32	29-09-2015	29-09-2015	29-09-2015 10:50	29-09-2015 11:47	08L	B77W	8.941.616	
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	OVERA	09L-LLZ	29-09-2015 11:44	UA054	UA	54	C1	A	75W	N14115	UAL54	29-09-2015	29-09-2015	29-09-2015 10:55	29-09-2015 11:44	09L	B752	5.707.671	
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	OVERD	27L	29-09-2015 11:40	AA063	AA	63	C2A	D	76W	N398AN	AAL63	29-09-2015	29-09-2015	29-09-2015 11:00	29-09-2015 11:40	09R	B763	8.005.700	

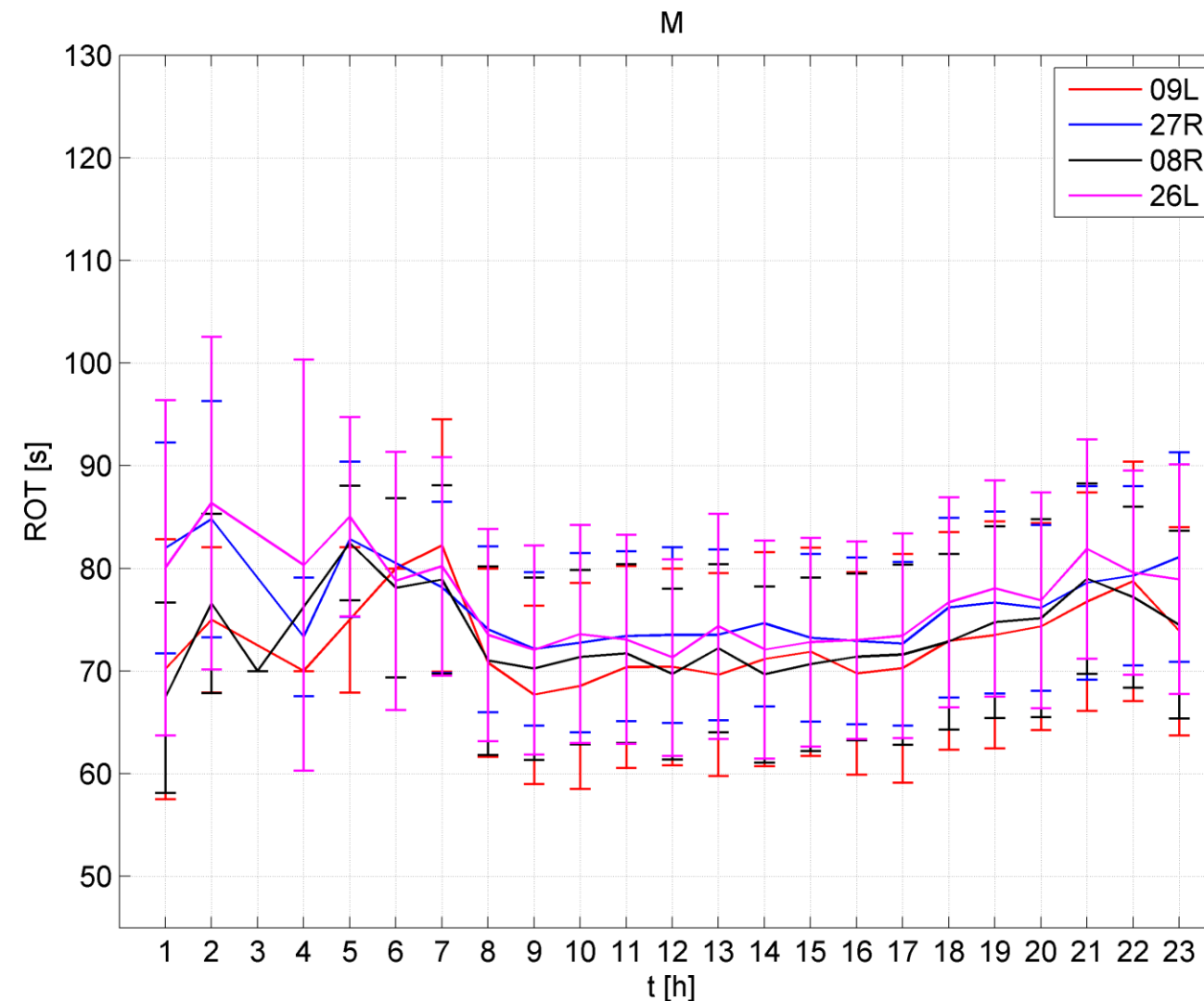
Methodology – Compute AROT

- Before feasible Machine Learning techniques can be applied the AROT response is extracted by calculating the time between the ALDT and the RWEF



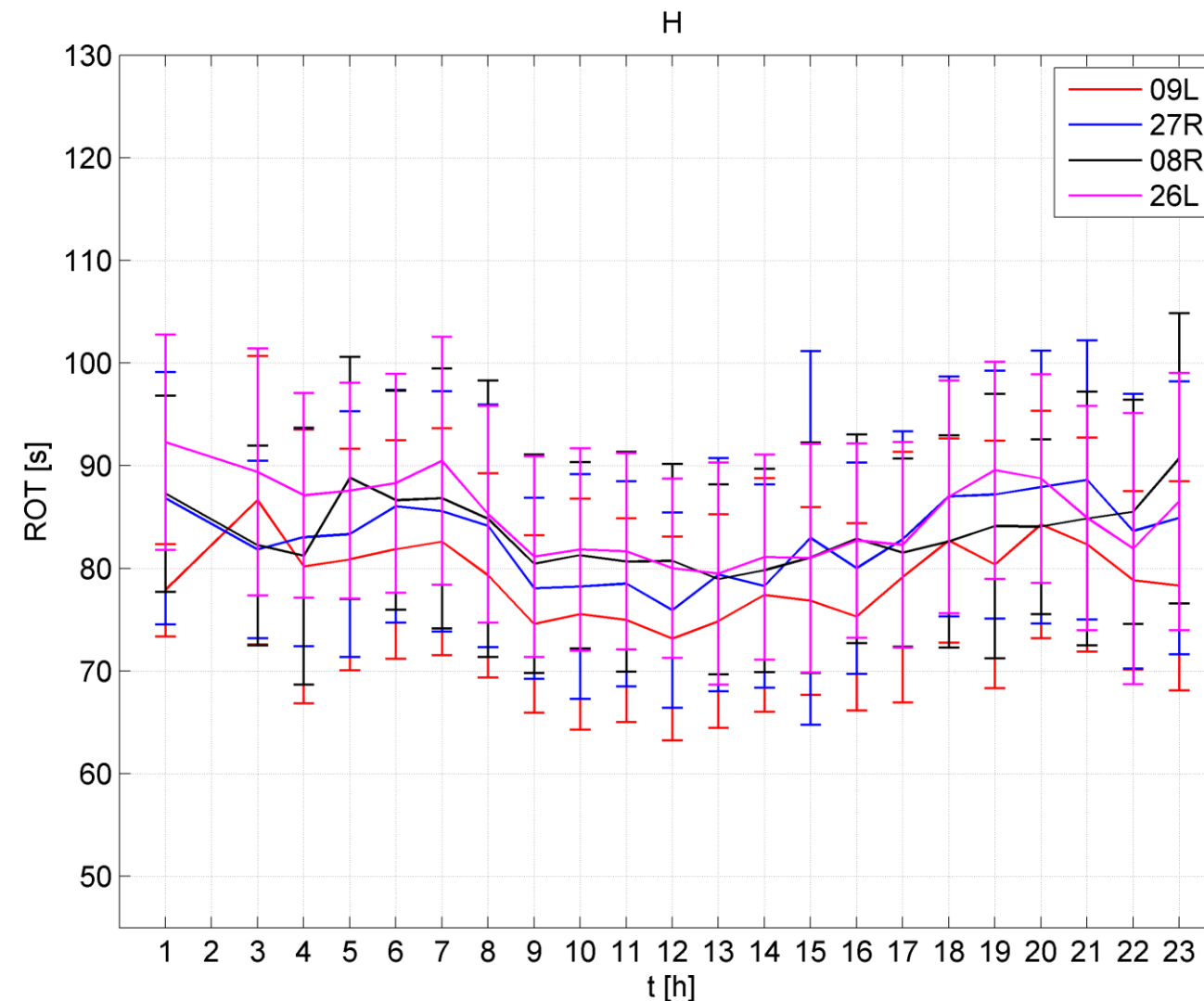
Methodology – Compute AROT

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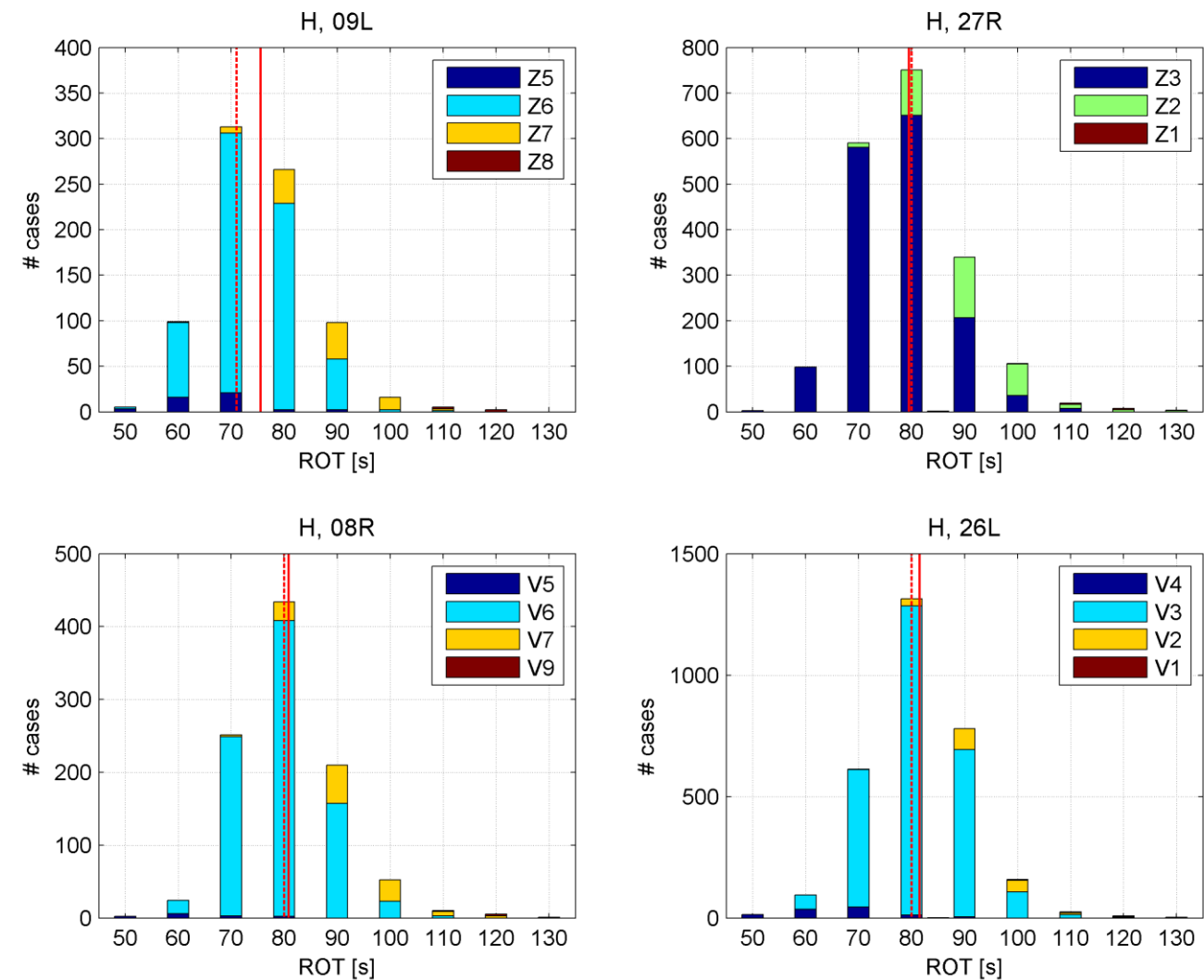
Methodology – Compute AROT

- Before feasible Machine Learning techniques can be applied the AROT response is extracted by calculating the time between the ALDT and the RWEF



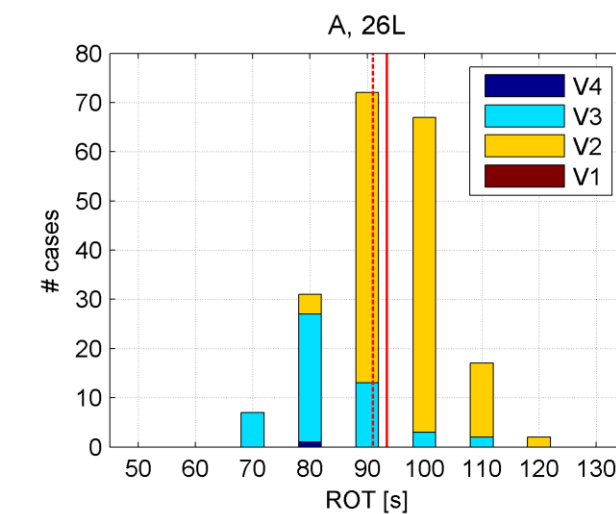
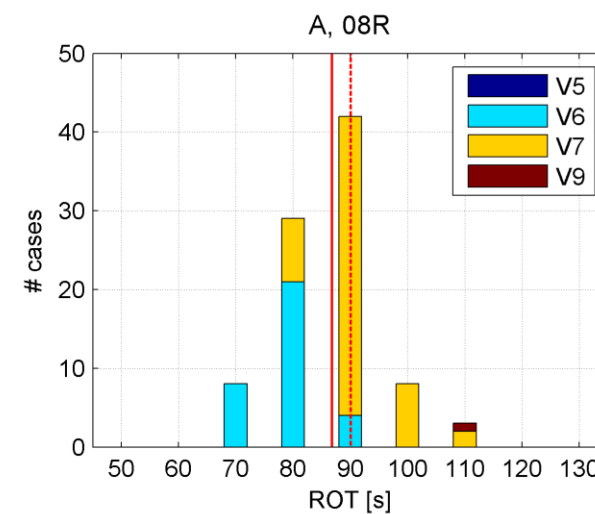
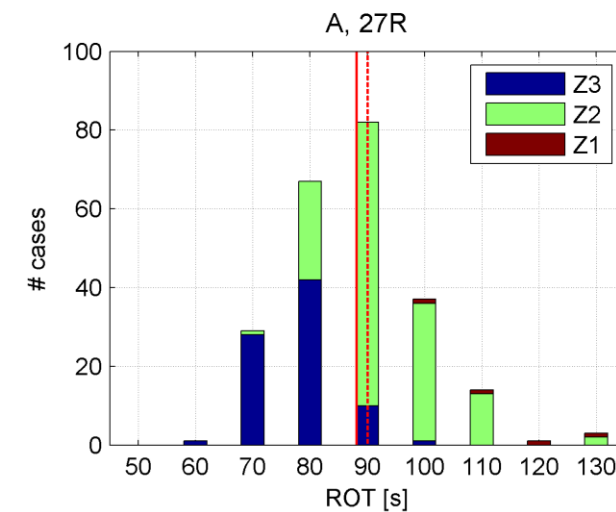
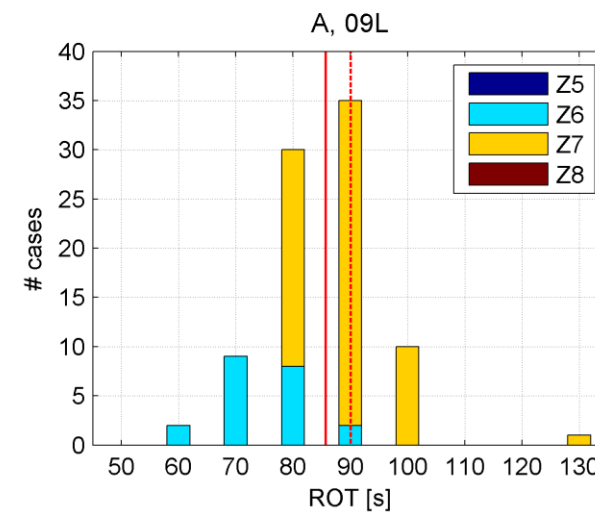
Introduction – What is AROT?

- AROT versus different CDG runway exits for ICAO and RECAT-EU



Introduction – What is AROT?

- AROT versus different CDG runway exits for ICAO and RECAT-EU



Data collection CDG and VIE

TXOT Prediction variables	Description
1. Anne	Year
2. Caractredevol	Commercial or private flight
3. CodeIATA	IATA code company
4. CodeAeroportOACI	OACI code
5. CodeAeroportICAO	ICAO code
6. CodeAeroportIATA	IATA code
7. CodeAeroportICAO	ICAO code
8. CodeAeroportIATA	IATA code
9. CodeAeroportICAO	ICAO code
10. CodeAeroportIATA	IATA code
11. CodeAeroportICAO	ICAO code
12. CodeAeroportIATA	IATA code
13. NumFlight	Number of flights
14. Postestationnement	Post stationnement
15. QFU	QFU
16. Semaine	Semaine
17. Tailwind	Tailwind
18. Temp	Temperature
19. TimeReal	Actual time of the day
20. Typeavion	Aircraft type
21. Visibility	METAR visibility conditions
22. ACSpeedPoint	Speed of the aircraft at 2NM, and 1NM out, Threshold and the Runway Exit Point (RWE)
23. ALDT	Actual Landing Time

Additional TXOT Prediction variables	Description
24. Arrival runway throughput	The amount of landings that is performed on the runway during the last 30 min

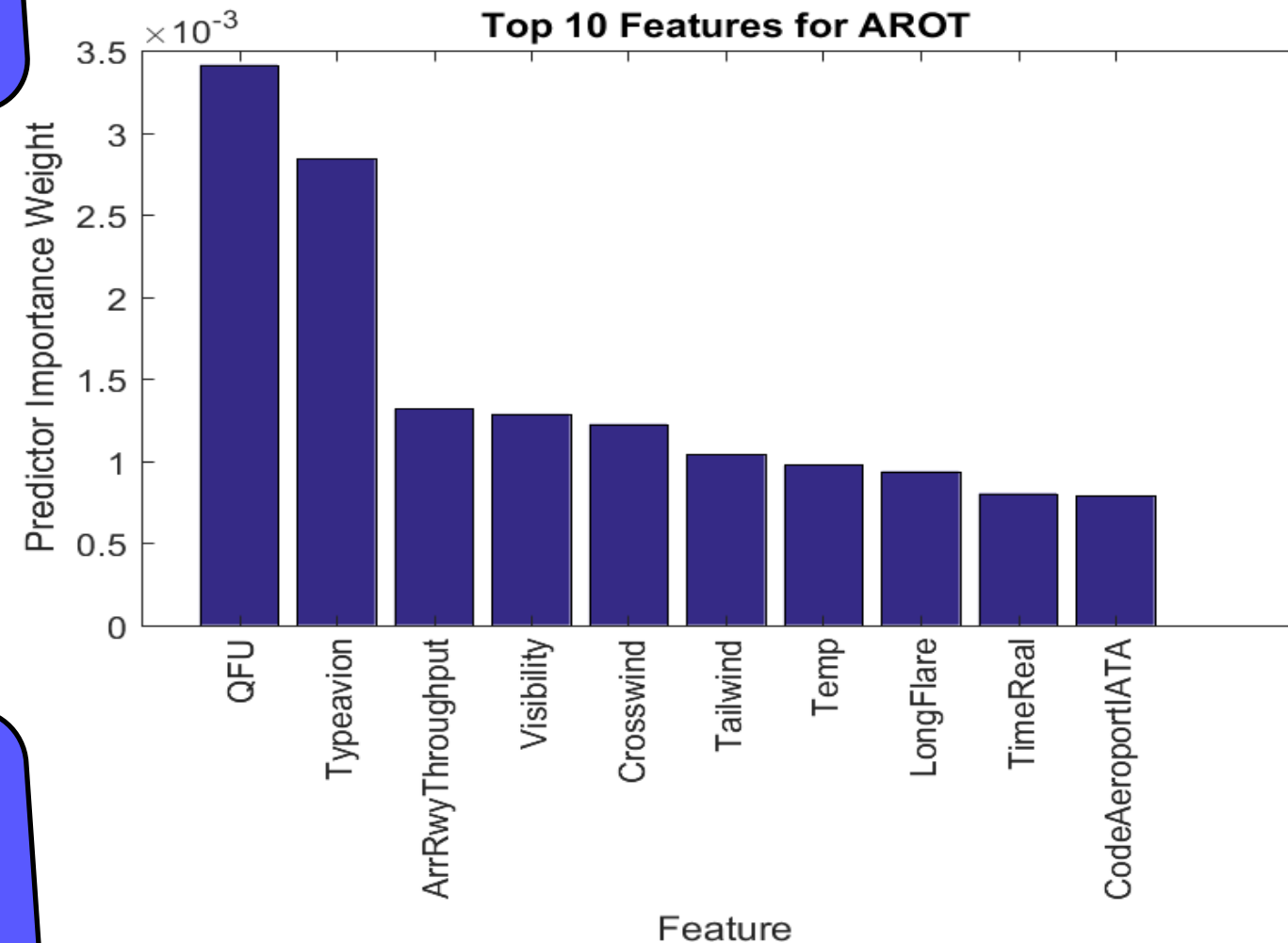
23 variables are used to train the model

ALDT and RWE are only used to extract the AROT response

1 variable is added to the model

Methodology – Data preparation

We had 22 variables



Consistent results leading to top 10 explanatory variables

Two feature selection techniques were applied

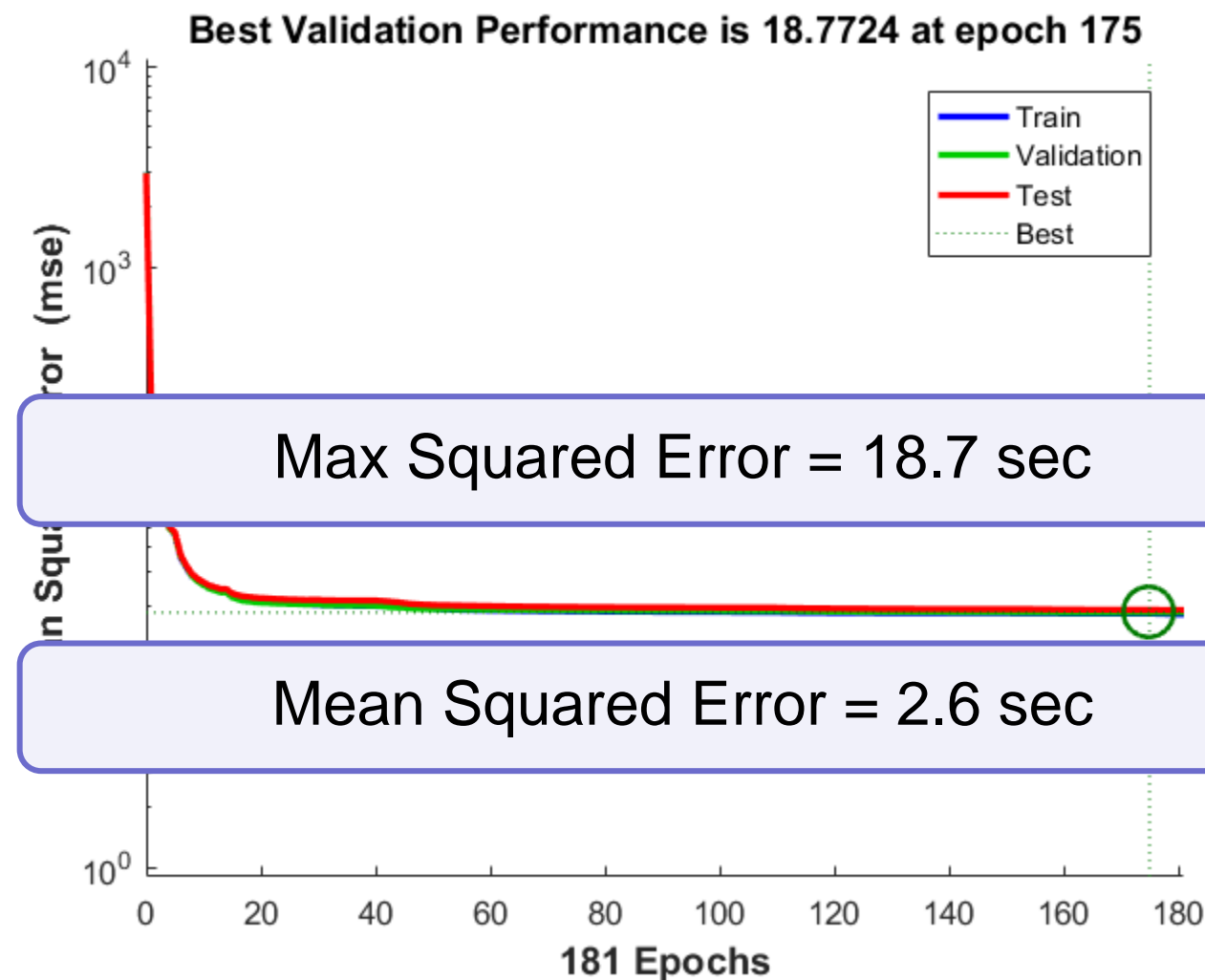
Top 3 variables:

1. QFU
2. Aircraft type
3. Arrival RWY throughput

Combined ML method

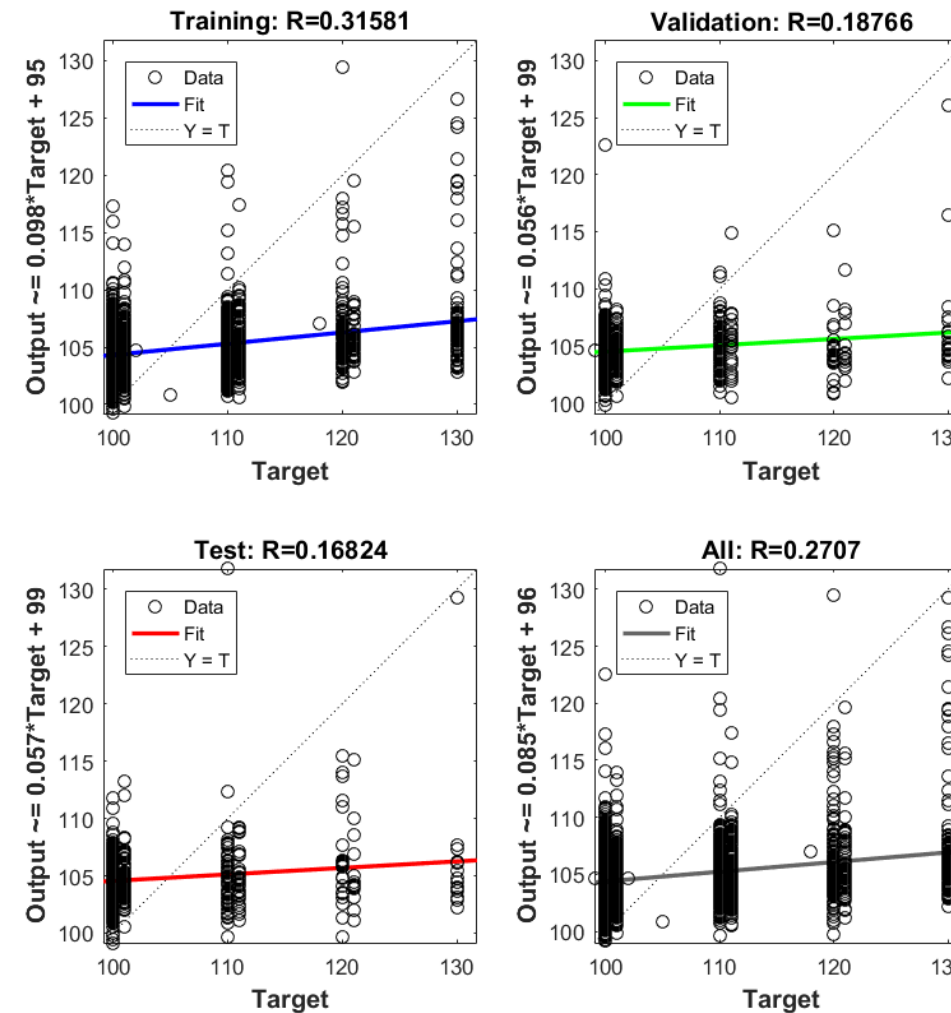
- First we learn the AROT for 350,000 flights with the top 10 features. Four models will be learned using the Lasso, Multi-Layer perception, Neural Networks and the Regression forests technique.
- Second we merge the predicted AROT results of all 4 models to one final matrix for 350,000 flights.
- Finally we apply the regression tree technique to the final matrix obtained in the previous step.
- Using 10 features instead of all features gives us a model that;
 - Has a faster computational time,
 - Is more robust to changes
 - Has a similar MSE

- After applying the regression tree technique the following performances are obtained



Methodology – Abnormal flights & Outliers

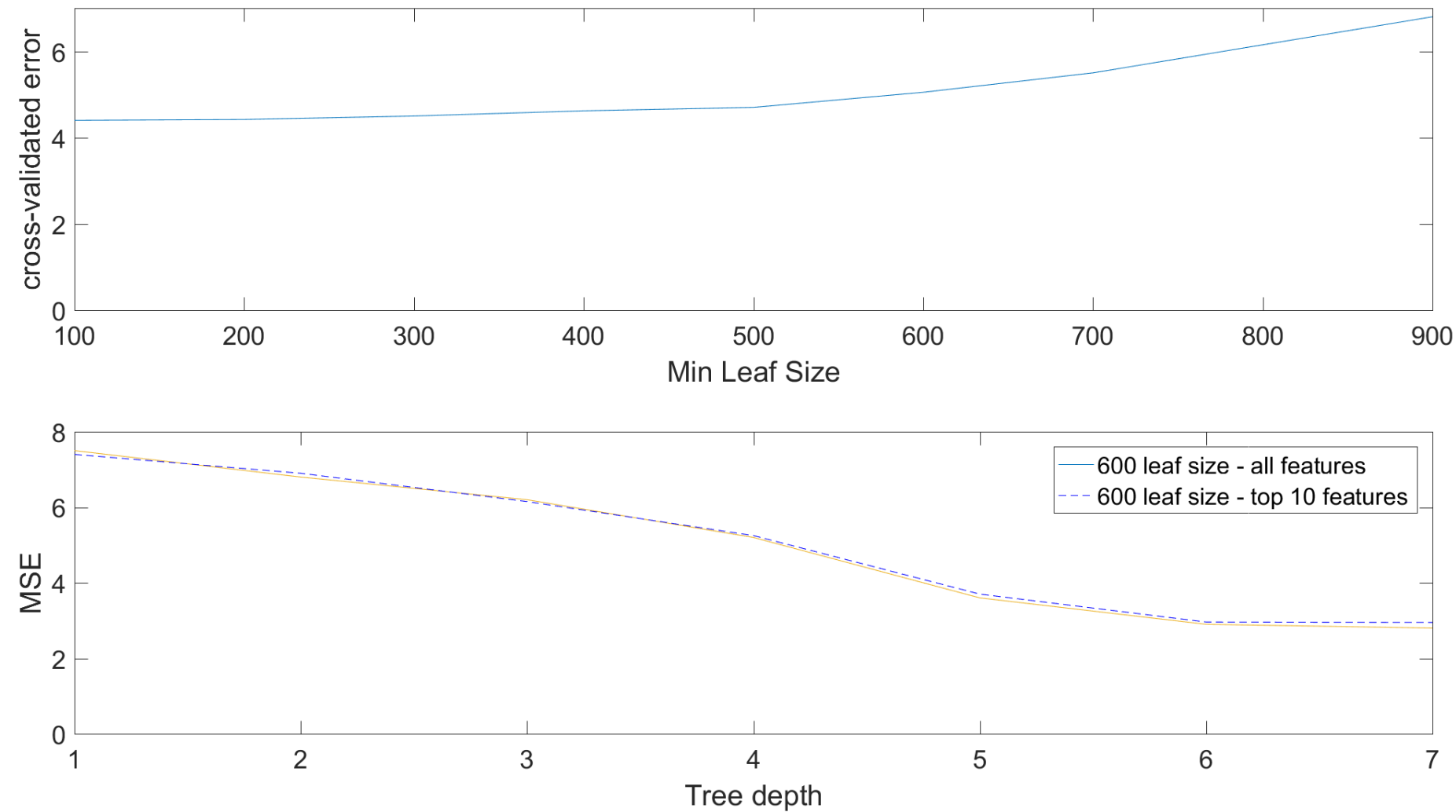
- An *abnormal* AROT is considered when it is $+2\sigma$ deviated from the normal standard deviation mean.



- Outliers example of *abnormal* AROT flights for training the model with 10 features.

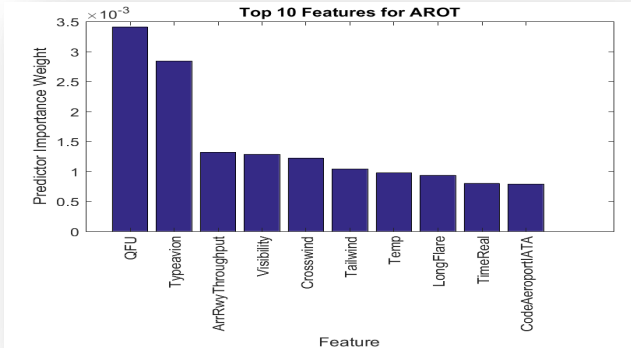
Methodology – Regression tree

- MSE versus Tree Depth for different leaf size and amount of features



Methodology – abnormal AROT regression tree

- During regression tree modelling we observe TXOT precursors which is done by extracting ‘what-if’ scenarios based on the 10 important features.



ArrRwyThroughput > 30

TypeAvion = Medium or (super) Heavy

Visibility < 805m

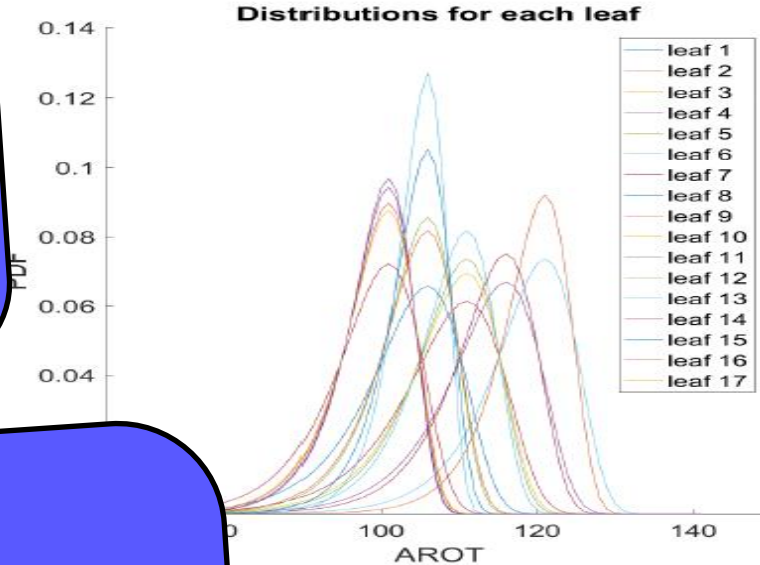
Air France A320 from London
Runway 08L
Start prediction 08:00
Update frequency 5 min
Number of simulations 1500

TypeAvion = Medium or (super) Heavy

Visibility < 805m

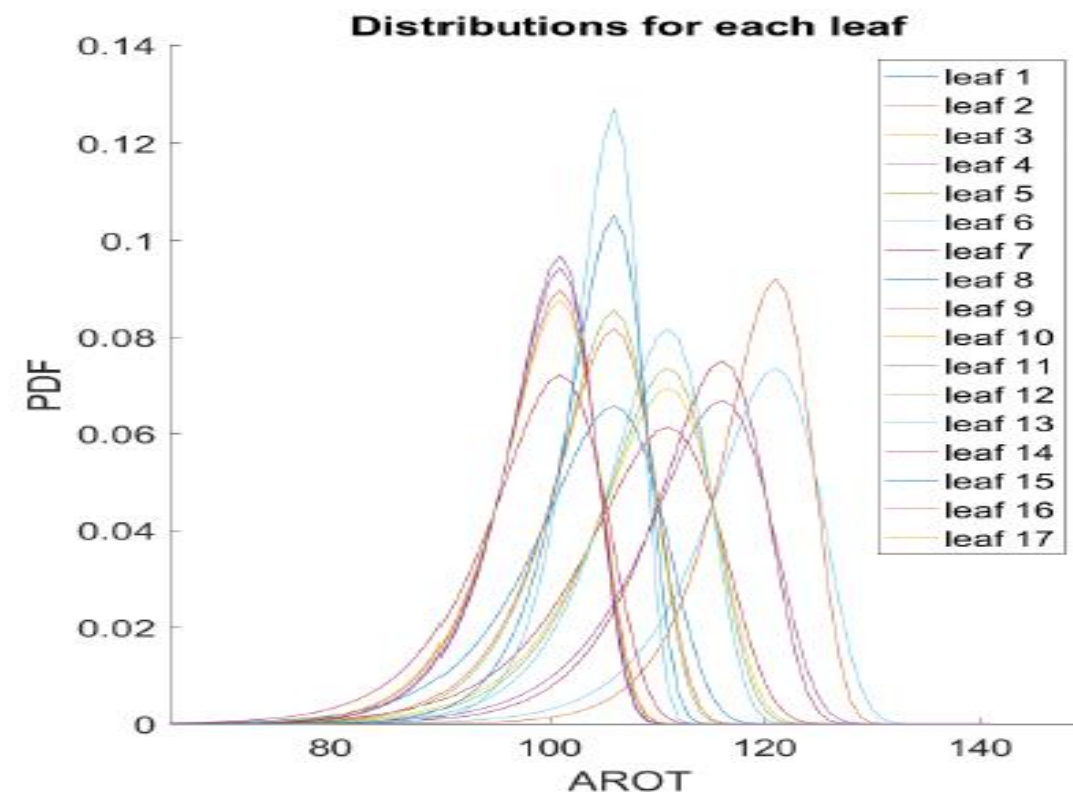
Temp > 14

1. ArrRwyThroughput < 30
2. TypeAvion = Medium
3. Visibility < 935 m
4. Crosswind > 14kts
5. Time between 07:00 and 09:00
AROT = 62 sec
MSE = 2.8 sec



AROT tree

- The probability distributions we considered for the terminal leaf nodes include the Normal, Gumbel, Gamma, and F distributions. The following equation shows the Gumbel distribution which fits best;



$$f(x) = \frac{1}{\beta} e^{-\left(\frac{x-\mu}{\beta} + e^{-\frac{x-\mu}{\beta}}\right)}$$

What do we do with this ?

- We know what influence what...
- Remember the question:
- Can we better predict the *abnormal* AROT profile?
 - for better predicting the go-arounds
 - for better predicting the number of landings
 - for better predicting the arrival runway throughput.

YES!



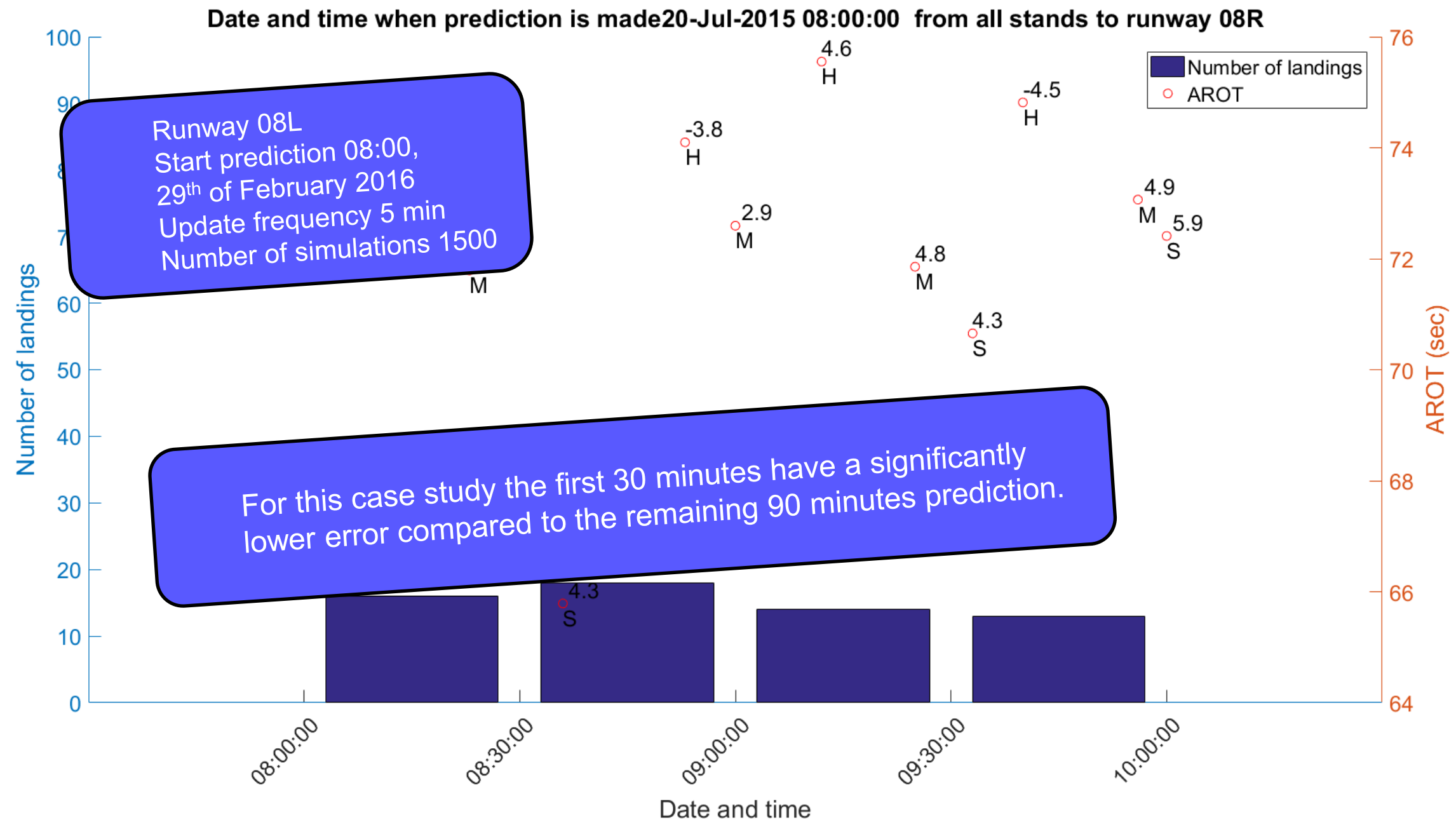
- Based on what we have learned in the previous steps and the data availability we develop a prototype model to forecast abnormal AROT at CDG and VIE.

```
Command Window

>> CDGRwyOccupancyTime
ML technique (Combine Lasso, Multi-Layer perception and Neural Networks (yes or no)):yes
Forecast window (min):120
Number of simulations:1500
Runway:08R
Forecast resolutions (separated with commas):1,5,15,60
Update frequency (min):5
Starting time to predict (YYYY-MM-DD HH:MM:SS):2015-07-20 08-00-00
fx Ending time to predict (YYYY-MM-DD HH:MM:SS):2015-07-20 14-00-00
```

- The operational data sets can be accessed in real time with exception of the actual variables; ALDT and RWEF

Methodology – Prototype model



Prototype model

- Average error differences per trial for the time prediction window 0-30 minutes and 30-90 minutes.

	0 - 30 minutes	30 - 90 minutes
Trial 1	6%	10%
Trial 2	4%	8%
Trial 3	4%	9%
Trial 4	2%	6%

Conclusion and Recommendations

- Machine learning techniques seem to be very effective in terms of abnormal AROT performance prediction.
- Predictions can be computed in just a few seconds after the tree has been extracted.
- Such predictions are useful for:
 - Tactical tool to alert ATC on extending ROT
 - Strategic tool to support ATC supervisor on;
 - Coordination of the runway configuration and changing of the sequence algorithm
 - Input AMAN/DMAN
- The methodology can easily be transposed to any other airport processes such as the prediction of the runway exit taken.
- As a next step we will include the runway condition and FDM data.

Thank you

Any questions?

- With this study a better prediction will be established of the AROT patterns and precursors, this research will stimulate further Dynamic Pair-wise Separation studies....

